A Time-Reversal Paradigm for Indoor Positioning System

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***Abstract*—In an indoor environment, there commonly exist a large number of multipaths due to rich scatterers. These multipaths make the indoor positioning problem very challenging. The main reason is that most of the transmitted signals are significantly distorted by the multipaths before arriving at the receiver, which causes inaccuracies in the estimation of the positioning features such as the time of arrival (TOA) and the angle of arrival (AOA). On the other hand, the multipath effect can be very constructive when employed in the time-reversal (TR) radio transmission. By utilizing the uniqueness of the multipath profile at each location, TR can create a resonating effect of focusing the energy of the transmitted signal only onto the intended location, which is known as the spatial focusing effect. In this paper, we propose exploiting such a high-resolution focusing effect in the indoor positioning problem. Specifically, we propose a TR indoor positioning system (TRIPS) by utilizing the location-specific characteristic of multipaths. By doing so, we decompose the ill-posed single-access-point (AP) indoor positioning problem into two well-defined subproblems. The first subproblem is to create a database by mapping the physical geographical location with the logical location in the channel impulse response (CIR) space, whereas the second subproblem is to determine the real physical location by matching the estimated CIR with those in the database. To evaluate the performance of our proposed TRIPS, we build a prototype to conduct real experiments. The experimental results show that, with a single AP working in the 5.4-GHz band under the non-line-of-sight (NLOS) condition, our proposed TRIPS can achieve perfect 10-cm localization accuracy with zero-error rate within a 0.9 m by 1 m area of interest.**

***Index Terms*—Indoor positioning system (IPS), multipath, spatial focusing, time reversal (TR).**

I. Introduction

With the advancement of communication technology, handheld devices such as mobile phones, tablets, and laptops have become an important and indispensable part of our daily lives. We use them to check emails, to connect to various social networks, and to watch video streaming, just to name a few. Since these devices can provide us with all-day connectivity through wireless communication techniques such as WiFi and Fourth-Generation Long Term Evolution (4G LTE), we carry them with us all the time, due to which it is possible to record and trace our activities by tracking these devices. Specifically, with the sensors installed in the handheld devices, one can gather various kinds of user information that can reveal users' behavior at different locations and time, e.g., users' location, movement, and data usage. Through analyzing these collected pieces of information, service providers can estimate and learn users' behaviors and preferences and, thus, provide user-specific services.

To successfully provide users with the right versatile services, it is crucial for the service provider to know the exact location of users. In the literature, many indoor positioning system (IPS) approaches have been developed, and most of them can be classified into three categories [1]: triangulation, proximity methods, and scene analysis. In triangulation, the terminal device (TD) measures the time of arrival (TOA) [2], the time difference of arrival [3], and the angle of arrival (AOA) [4], [5] of the signals sent from the access point (AP) with known positions and then uses physical principles of wave propagation to calculate the geographical location based on the measurements. Although the concept of triangulation is simple, some special requirements are needed, e.g., precise measurements of TOA and/or AOA, synchronization between the TD and the AP, and specialized apparatus for AP. However, due to the rich scattering characteristic of an indoor environment, the measurements are generally not very precise, which leads to poor indoor positioning performance of these triangulation methods.

The second category of IPS algorithms is a proximity method that can provide symbolic relative location information. This kind of algorithms relies on the dense deployment of the infrastructure. When the TD moves in the target area, the TD is considered to be located with the antenna that detects the TD. If multiple antennas can detect the TD, then the TD is simply considered to be located with the antenna that receives the strongest signal. Most of the radio-frequency (RF) identification and the cell identification [6] positioning systems fall into this category. Since the TD will be considered to be colocated with the antenna, this kind of algorithms cannot give precise location information. Moreover, due to the dense deployment of the antennas, the implementation cost is very high.

The third category of IPS algorithms is the scene analysis method, which first collects features of the scene and then matches online measurements with the collected features to estimate the location. Most of the scene analysis-based IPS algorithms make use of the received signal strength (RSS) and/or the

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channel state information (CSI), whereas the matching method can be either deterministic or probabilistic [7]. In a deterministic method, the position is determined by finding the minimum distance between the measurements to the database. In [8], it was proposed to first use spatial filtering to reduce the number of reference APs and then use kernel functions as distance measures. A root-mean-square error of 2.71 m was reported using three APs. An RF-based tracking system named RADAR was proposed in [9]. The system uses empirically determined and theoretically computed signal strength for triangulation, and triangulation is done using the signal strength information gathered at multiple locations. A median resolution was reported to be in the range of 2–3 m using three APs. A linear approximation model on the RSS versus the Euclidean distance between the AP and the TD in an anonymous environment without necessary offline training was proposed in [10] and achieves a mean estimation error of 15 m. A compressive sensing scheme was proposed in [11] for localization using the sparsity characteristics in positioning problems with 1.5-m error.

On the other hand, in a probabilistic method, the estimation is based on some probabilistic criteria such as maximum *a posteriori* (MAP) and maximal likelihood (ML). In [12] and [13], a positioning algorithm based on WiFi RSS was proposed. The RSS information from multiple WiFi APs is collected, and the distribution of the RSS is estimated. During the online positioning phase, the MAP or ML criterion is used to determine the location and achieve a mean error of 40 cm with multiple APs. In [14], the RSS of WiFi and FM signals was used to jointly estimate the cumulative distribution function of RSS for indoor positioning. The smaller variation of FM signals in an indoor environment provides extra information and precision over WiFi-only systems and achieves better room-level accuracy. In addition to the RSS, the CSI has been also used in the literature for positioning. In [15], it was proposed to use the amplitude of channel impulse response (CIR) as the fingerprint for localization. The amplitude of CIR is used as an input to a nonparametric kernel regression method for location estimation. In [16] and [17], it was proposed to utilize the complex CIR as a link signature for location distinction, where the normalized minimal Euclidean distance is adopted as the distance measure. The CSI was proposed to be used in the orthogonal frequency-division multiplexing (OFDM) systems as the fingerprints in the positioning algorithm [18]. Since there are a lot of partitioned channels in an OFDM system, the CSI provides rich information for positioning. In the online phase, the CSI from the TD is matched to the stored database using a MAP algorithm. The authors report a mean accuracy value of 65 cm in a 5 m by 8 m office using three APs.

However, most of the existing IPS algorithms cannot achieve a desired centimeter-level localization accuracy value, particularly for a single AP working in the non-line-of-sight (NLOS) condition. The main reason is that it is generally very difficult or even impossible to obtain precise measurements due to the rich scattering indoor environment. Such imprecise measures lead to ambiguity when performing positioning algorithms. To reduce ambiguity, most existing algorithms require more online measurements and/or multiple APs. Different from the existing approaches, in this paper, we propose a single-AP indoor positioning algorithm that can achieve centimeter-level localization accuracy with single realization of online measurement by utilizing the time-reversal (TR) technique. TR technique is known to be able to focus the energy of the transmitted signal only onto the intended location, i.e., the spatial focusing effect. The foundation of spatial focusing is that the CIR in a rich scattering indoor environment is location specific and unique for each location [19], i.e., each CIR corresponds to a physical geographical location. Therefore, by utilizing such a unique location-specific CIR, the proposed TR indoor positioning system (TRIPS) is able to position the TD by matching the CIR with the geographical location. Since spatial focusing is a half-wavelength focus spot, the proposed TRIPS can achieve a centimeter-level localization accuracy value even with a single AP working in the NLOS condition.

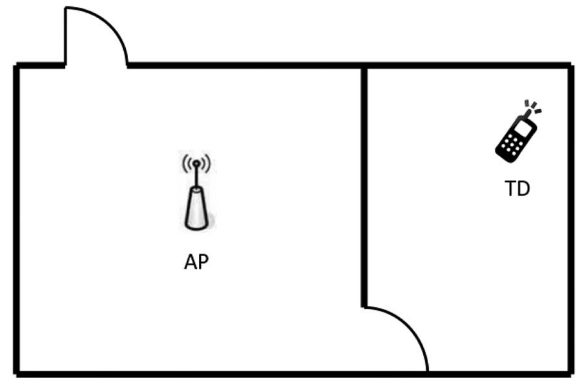


Fig. 1. System model.

The rest of this paper is organized as follows. In Section II, we will briefly review the TR technique and describe in detail the proposed TRIPS. Then, in Section III, we will discuss the experimental results, including the properties of the TR technique and the performance of the proposed TRIPS. Finally, we draw conclusions in Section IV.

II. Time-Reversal Indoor Positioning System

As shown in Fig. 1, we study the indoor localization problem where there is an AP and a TD in an indoor environment. The AP is positioned in an arbitrarily known location, whereas the location of the TD is unknown. The TD transmits some known signals, e.g., fixed pseudorandom sequences, to the AP, and the AP tries to estimate the location of the TD based on the received signals. Due to the multipaths in the indoor environment, the received signal at the AP is significantly distorted [12]. In such a case, it is generally impossible to identify the location purely based on the received signal of a single AP, i.e., the single-AP indoor localization problem is ill posed.

To address this problem, we propose a TRIPS by decomposing the ill-posed problem into two well-defined subproblems. Specifically, in the first subproblem, we build a database offline by mapping the physical geographical locations to the logical locations in the CIR space. Then, in the second subproblem, we match the online estimated CIR of the TD to those in the database to position the TD. In the following sections, we first give a brief introduction of the TR technique and then discuss in detail the proposed TR-based indoor positioning system.

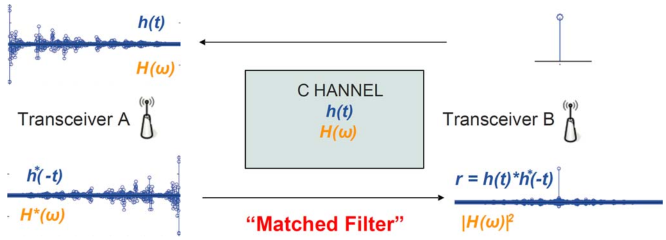


Fig. 2. TR signal processing principle.

A. Background of TR

TR is a technology that can focus the power of the transmitted signal in both time and space domains. The phenomenon of TR was first observed by Zel'dovich *et al.* in 1985 [20]. Later, the TR technique was studied and applied into signal processing by Fink *et al.* in 1989 [21], followed by several theoretical and experimental works in acoustic and ultrasonic communications, verifying that the transmitted wave energy can be focused at the intended location with high spatial and temporal resolution [22]–[24]. Due to the fact that TR does not require complicated channel processing and equalization, it was also analyzed, tested, and validated in wireless communications [19], [25]–[35]. Moreover, with a potential of over an order of magnitude of reduction in power consumption and interference alleviation, as well as the natural capability of supporting heterogeneous TDs and providing an additional security and privacy guarantee, TR technique is shown to be a promising solution for green Internet of Things [36].

Fig. 2 demonstrates a simple TR communication system [19]. When transceiver A wants to transmit information to transceiver B, transceiver B first sends an impulse signal to transceiver A. This is called the channel probing phase. Then, transceiver A time-reverses (and conjugates if the signal is complex) the received waveform from transceiver B and uses the time-reversed version of waveform to transmit the information back to transceiver B. This second phase is called the TR transmission phase.

The TR technique relies on two basic assumptions, i.e., channel reciprocity and channel stationarity. Channel reciprocity requires the CIRs of the forward and backward links to be highly correlated, whereas channel stationarity requires the CIR to be stationary for at least one probing-and-transmission phase. These two assumptions generally hold in practice, as validated by experiments in [27] and [19]. In [27], an experiment was conducted in a laboratory area and showed that the correlation of CIR between the forward and backward links is as high as 0.98, whereas in [19], it was shown that the multipath channel in a typical office environment does not vary much over time. Specifically, the CIR had a snapshot once every minute for a total of 40 min, where the first 20 snapshots correspond to a stationary environment, the 21st to 30th snapshots correspond to a moderately varying environment, and the last 10 snapshots correspond to a varying environment. The experimental results show that the correlation coefficients between different snapshots are above 0.95 for a stationary environment and above 0.8 for a varying environment.

With the property of the channel reciprocity and stationarity, the re-emitted TR signal will retrace the incoming paths and form a constructive sum of signals at the intended location, resulting in a peak in the signal–power distribution over the space, i.e., spatial focusing effect. Since TR utilizes all the multipaths as a matched filter, the transmitted signal will be focused in the time domain, which is referred as the temporal focusing effect. Moreover, by using the environment as matched filters, the transceiver design complexity can be significantly reduced. In an indoor environment, the wireless multipaths come from the surrounding reflectors. Since the received waveforms from the TD at different locations undergo different reflecting paths and delays, the multipath profile is unique for each location. By utilizing this unique location-specific multipath profile, TR can create the spatial focusing effect at the intended location, i.e., the received signals are added coherently at the intended location but incoherently at any unintended location. As will be discussed in the next section, our proposed algorithm leverages such a special feature to solve the ill-posed single-AP indoor localization problem.

B. Proposed TR Indoor Positioning Algorithm

Here, we will discuss in detail the proposed TR indoor positioning algorithm. With the spatial focusing effect, we know that the CIR in the TR system is location specific, which means that we can map the physical geographical locations into logical locations in the CIR space where one physical geographical location corresponds to a unique CIR in the TR system. Then, the indoor localization problem becomes a classical classification problem that identifies the class of the TD in the CIR space. Therefore, the proposed TR indoor positioning algorithm contains two phases. The first phase is an offline training phase where we build a CIR database to map the physical geographical location into the logical location in the CIR space, and the second phase is an online positioning phase where we match the estimated CIR of the TD with the CIR database to localize the TD.

1) Offline Training Phase: In the offline training phase, we are building a CIR database for the online positioning phase. Since the database has a direct consequence to the localization performance, how to build the database is critical to the proposed indoor positioning algorithm. Note that the CIR at different locations will be different if the distance between two locations is larger than the wavelength and may be similar if the distance is smaller than the wavelength. Moreover, the CIR at a certain location may slightly vary over time due to the change of environment. With such an intuition, for each intended location, we obtain a series of CIRs at different time. Specifically, for each intended location p_i, we collect the CIRs' information $\mathbf{H}_i$ as follows:

$$\mathbf{H}_i = \{\mathbf{h}_i(t = t_0), \mathbf{h}_i(t = t_1), \ldots, \mathbf{h}_i(t = t_M)\} \quad (1)$$

where $\mathbf{h}_i(t = t_l)$ stands for the estimated CIR information on location p_i at time t_l.

Therefore, the database $\mathbf{D}$ is the collection of all $\mathbf{H}_i'$

$$\mathbf{D} = \{\mathbf{H}_i \forall i\}. \quad (2)$$

2) Online Positioning Phase: In the online positioning phase, we first estimate the CIR information based on the signal received at the AP. Then, our objective is to localize the TD by matching the estimated CIR information with the database using a classification technique. Since the dimension of the information for each location in the database is very high, classification based on the raw CIR information may not work. Therefore, it is necessary to preprocess the CIR information to obtain important features for the classification.

As we have previously discussed, since the received signals undergo different reflecting paths and delays for the receiver at different locations, the CIR can be viewed as a unique location-specific signature. When convolving the time-reversed CIR with the CIR in the database, only that at the intended location will produce a peak, which is known as spatial focusing effect. For the locations other than the intended location, there is no focusing effect. Therefore, we can design a TR-based dimension reduction approach to extract the effective feature for localization. To do so, we first introduce a definition of *TR resonating strength* as follows.

Definition 1 (TR Resonating Strength): The TR resonating strength $\eta(\mathbf{h}_1, \mathbf{h}_2)$ between two CIRs $\mathbf{h}_1 = [h_1[0], h_1[1], \ldots, h_1[L-1]]$ and $\mathbf{h}_2 = [h_2[0], h_2[1], \ldots, h_2[L-1]]$ is defined as

$$\eta(\mathbf{h}_1, \mathbf{h}_2) = \frac{\max_i |(\mathbf{h}_1 * \mathbf{g}_2)[i]|}{\sqrt{\sum_{i=0}^{L-1} |h_1[i]|^2} \sqrt{\sum_{j=0}^{L-1} |g_2[j]|^2}} \tag{3}$$

where $\mathbf{g}_2 = [g_2[0], g_2[1], \ldots, g_2[L-1]]$ is defined as the time-reversed and conjugated version of $\mathbf{h}_2$ as follows:

$$g_2[k] = h_2^*[L-1-k], \; k = 0, 1, \ldots, L-1. \tag{4}$$

A close look at (3) would reveal that the TR resonating strength is the maximal amplitude of the entries of the cross correlation between two complex CIRs, which is different from the conventional correlation coefficient between two complex CIRs where there is no $\max$ operation and the index $[i]$ in (3) is replaced with index $[L-1]$. The main reason for using the TR resonating strength instead of the conventional correlation coefficient is to increase the robustness for the tolerance of channel estimation error. Note that most of the channel estimation schemes may not be able to perfectly estimate the CIR due to the synchronization error, i.e., a few taps may be added or dropped during the channel estimation process. In such a case, the conventional correlation coefficient without $\max$ operation may not reflect the true similarity between two CIRs, whereas our proposed TR resonating strength is able to capture the real similarity and, thus, increase the robustness.

With the definition of TR resonating strength, we are now ready to describe the online positioning phase. Let $\hat{\mathbf{h}}$ be the CIR that we estimate for the TD with unknown location. To match $\hat{\mathbf{h}}$ with the logical locations in the database, we first extract the feature using the TR resonating strength for each location. Specifically, for each location p_i, we compute the maximal TR resonating strength η_i as follows:

$$\eta_i = \max_{\mathbf{h}_i(t=t_j) \in \mathbf{H}_i} \eta\left(\hat{\mathbf{h}}, \mathbf{h}_i(t=t_j)\right). \tag{5}$$

Fig. 3. Radio stations of the proposed TR system prototype.

By computing η_i for all possible locations, i.e., $\mathbf{H}_i \in \mathbf{D}$, we can obtain $\eta_1, \eta_2, \ldots, \eta_N$. Then, the estimated location $p_{\hat{i}}$ is simply the location that can give the maximal η_i, i.e., $\hat{i}$ can be derived as follows:

$$\hat{i} = \arg\max_i \eta_i. \tag{6}$$

Although our proposed algorithm is very simple, it can achieve very good localization performance, as we will see in the experiment in the next section.

III. Experiments

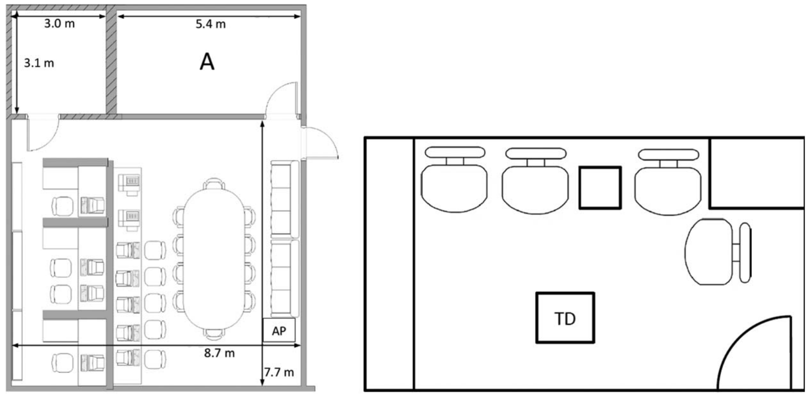
A. Experimental Setting

To evaluate the performance of our proposed algorithm, we build a TR system prototype that operates at 5.4-GHz band with a bandwidth of 125 MHz. A snapshot of the radio stations of our prototype is shown in Fig. 3, where the antenna is attached to a small cart with RF board and computer installed on the cart. We test the performance of our prototype in a typical office room that is located on the second floor of the Jeong H. Kim Engineering Building at the University of Maryland College Park. The layout of the floor plan of the office room is shown in Fig. 4(a), where the AP is located at the place with the mark "$\mathbf{AP}$" and the TD is located in the smaller office room marked as "$\mathbf{A}$." The detailed floor layout of room A is shown in Fig. 4(b). Notice that with such a setting, the AP is working in the NLOS condition.

B. Evaluation of TR Properties

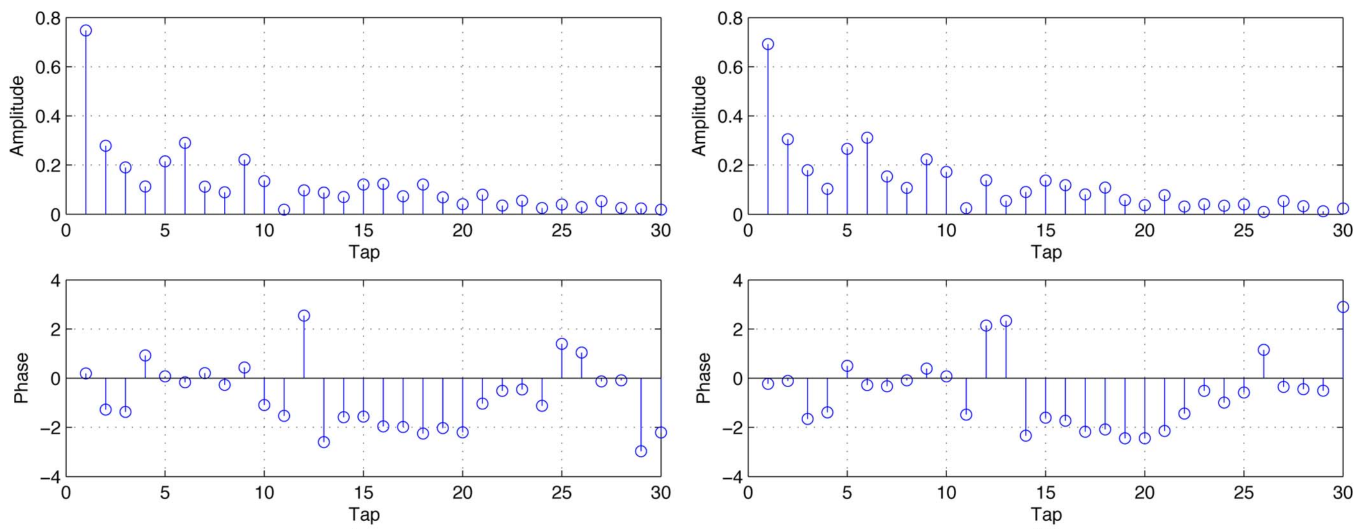
Here, we evaluate three important properties of the TR system, namely, channel reciprocity, temporal stationarity, and spatial focusing. Note that channel reciprocity and temporal stationarity are the two underlying assumptions of TR system, whereas spatial focusing is the key feature for the success of the proposed TRIPS.

1) Channel Reciprocity: We explore channel reciprocity by examining the CIR of the forward and backward links between the TD and the AP. Specifically, the TD first transmits a channel probing signal to the AP, and the AP records the CIR of the forward link. Immediately after that, the AP transmits a channel probing signal to the TD, and the TD records the CIR of the



(a) (b)

Fig. 4. (a) Floor plan of the office room where we conduct our experiments. (b) Floor plan of room A.



(a) (b)

Fig. 5. Evaluation of channel reciprocity. (a) CIR of the forward link. (b) CIR of the backward link.

backward link. These procedures are repeated 18 times. One CIR realization of forward and backward links is shown in Fig. 5, where (a) shows the amplitude and phase of the forward channel and (b) shows those of the backward channel. In these figures, we can see that the forward and backward channels are very similar. By computing the correlation between the CIR of the forward link and that of the backward link, as shown in Fig. 6, we can see that, indeed, the forward and backward channels are highly reciprocal. Fig. 7 shows the TR resonating strength η between any of the 18 forward and backward channel measurements with mean η to be over 0.95. This result shows that the reciprocity is stationary over time.

2) Channel Stationarity: We then evaluate the channel stationarity of the TR system by measuring the CIR of the link from the TD to AP under three different settings: short-interval, long-interval, and dynamic environments with a person walking around. In the short-interval experiment, we measure the CIR repeatedly 30 times, and the duration between two consecutive measurements is 2 min. For the long-interval experiment, we collect a total of 18 CIRs with 1-h interval from 9 A.M. to

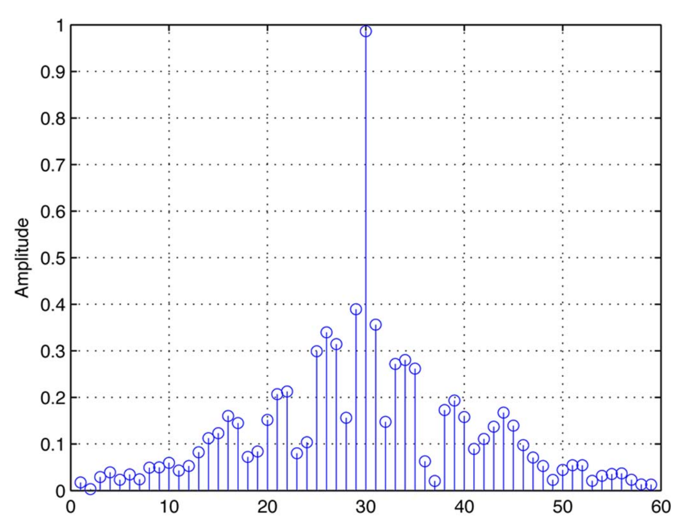


Fig. 6. Cross correlation between the CIR of the forward link and that of the backward link. Note that the center tap is the TR resonating strength between the CIR of the forward link and that of the backward link.

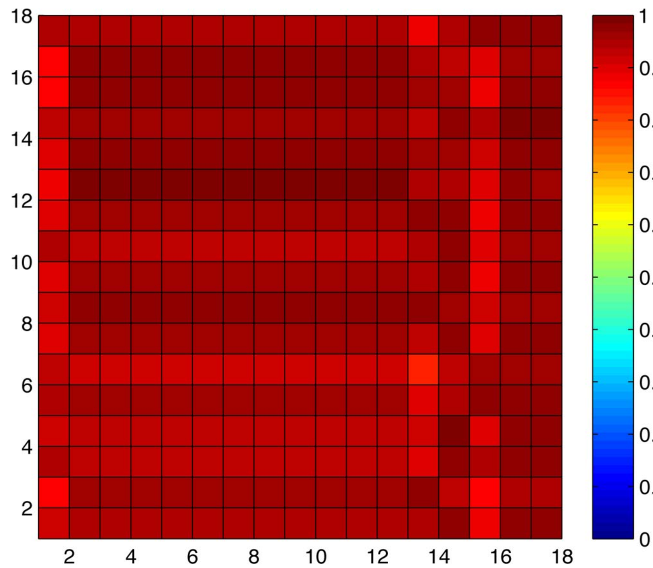


Fig. 7. TR resonating strength between CIRs of the forward link and those of the backward link.

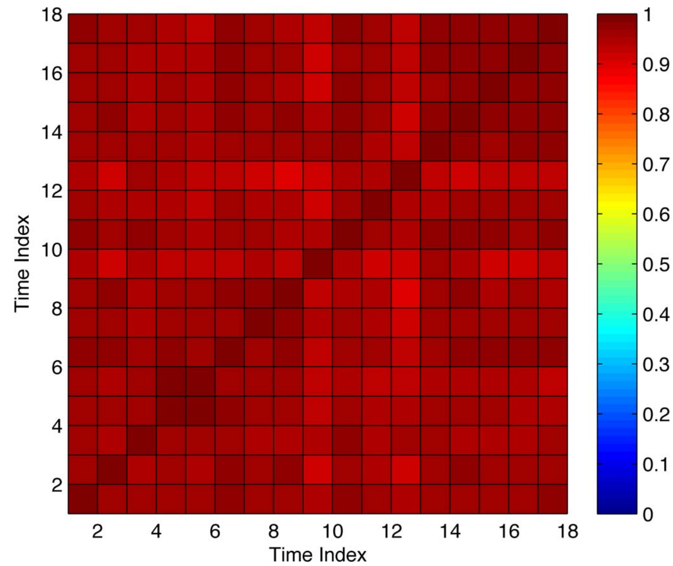


Fig. 9. Evaluation of long temporal stationarity using the TR resonating strength between any two CIRs from the 18 CIRs collected over a weekend between the AP and the TD.

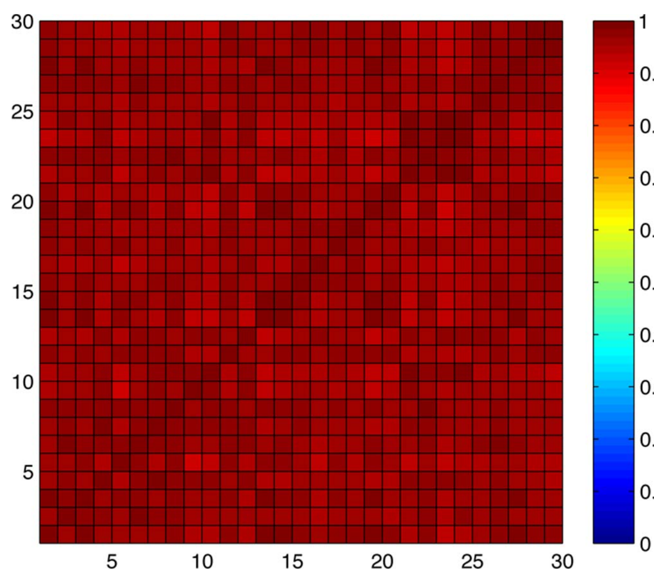


Fig. 8. Evaluation of short temporal stationarity using the TR resonating strength between any two CIRs from the 30 CIRs of the link between the TD and the AP.

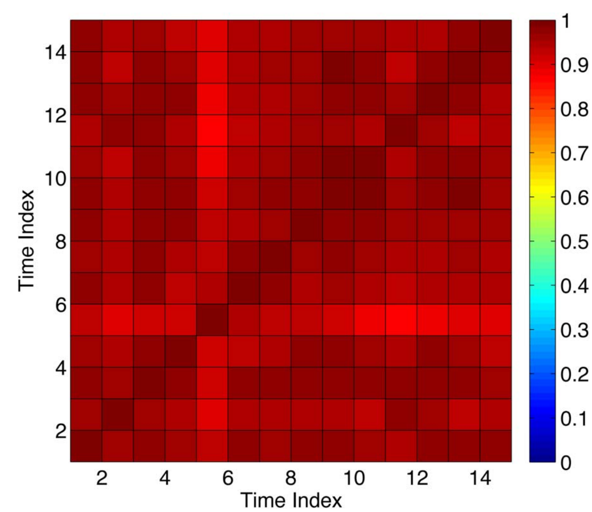


Fig. 10. Evaluation of channel stationarity under minor environment change using TR resonating strength between any two CIRs collected with a person walking around.

5 P.M. over a weekend. Fig. 8 shows the TR resonating strength η between any two CIRs from all 30 CIRs in the short-interval experiment, and Fig. 9 shows the TR resonating strength η between any two CIRs from the 18 CIRs collected in the long-interval experiment. We can see that the CIRs at different time instances are highly correlated for both the short interval and long interval, which means that the channel in an ordinary office does not vary much over time even with long duration. We then investigate the effect of human movement. We collect, every 30 s, the CIRs with a person walking randomly between the AP and the TD. Fig. 10 shows the TR resonating strength η between the 15 collected CIRs. The experimental result shows that, even with a person walking around, the TR resonating strength remains high among all of the collected CIRs. Therefore, the proposed TR positioning system does not require a frequent update of the CIR information. All these results are consistent with the observations in [19], the main reason being that the multipaths come from the refractions and reflections of the indoor environment, which are quite stable, as long as there is no severe disturbance of the environment.

3) Spatial Focusing: As we have previously discussed, the CIR comes from the surrounding scatterers and such scatterers are generally different for different geographical locations. Therefore, the CIR is location specific and unique for each location. By utilizing such a unique location-specific CIR, TR can focus the transmitted power only to the intended location, which is known as the spatial focusing effect of the TR system. We quantify such a spatial focusing effect using the maximum energy that the TD can harvest from the AP. To evaluate the spatial focusing effect, we conduct experiments by moving the locations of the TD on a 3-D architecture, as shown in Fig. 11, within a 1 m by 0.9 m area in room A. The grid points are 10 cm apart, which leads to 110 evaluated locations in total.

Fig. 11. Three-dimensional architecture for moving the locations of the TD.

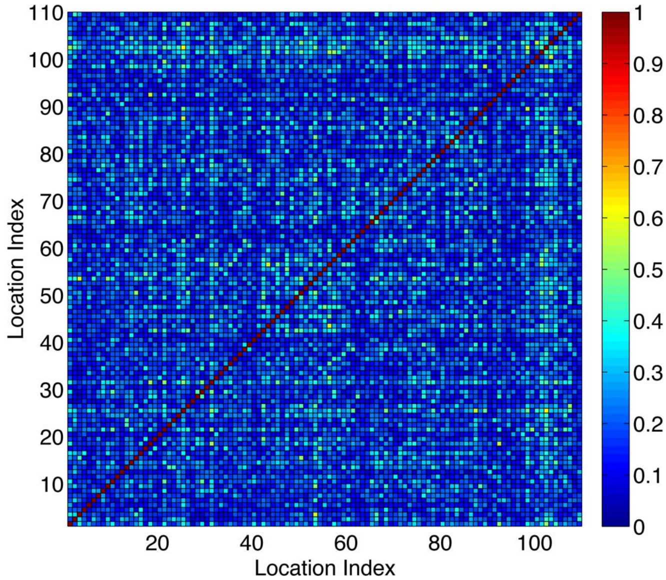


Fig. 12. Focusing gain η^2 of all grid points by moving the intended location within 1 m by 0.9 m area. Every dot in the figure stands for one grid point where two neighboring grids points are 10 cm away from each other. The horizontal/vertical axis is the location index with 1-D representation. Each value in (i, j) represents the focusing gain at location j (location index with 1-D representation) when the intended location is i (location index with 1-D representation).

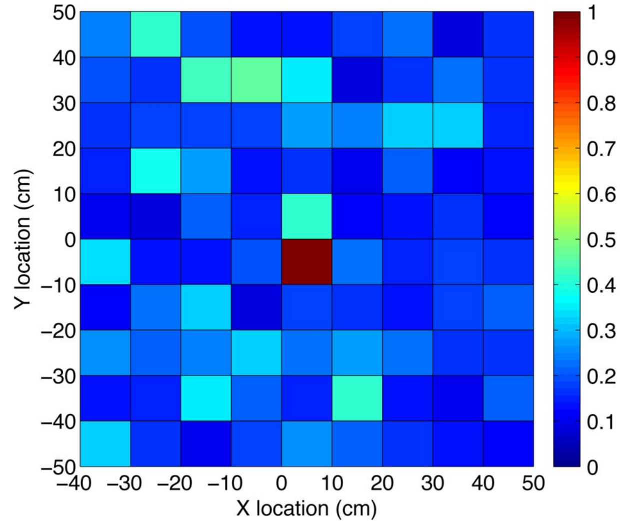


Fig. 13. Geographic distribution of η^2 with the intended location at the center of the area of interest.

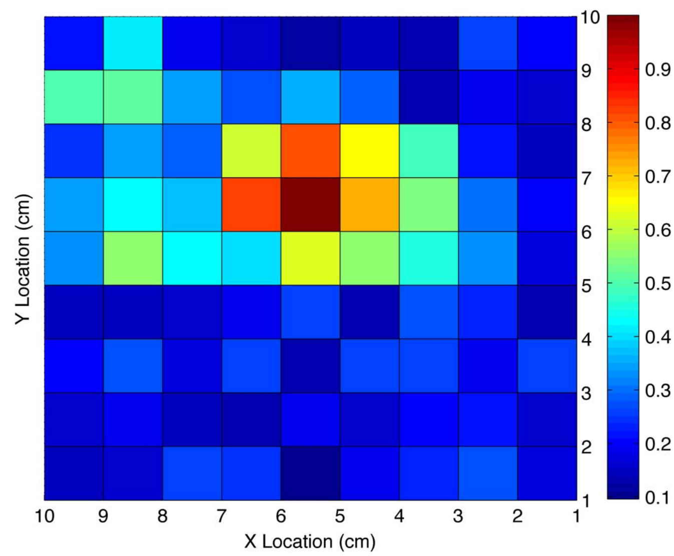


Fig. 14. Fine-scale geographic distribution of η^2.

We collect the CIR of all evaluated locations and compute the focusing gain, which is defined as the square of the TR resonating strength, i.e., η^2, by varying the intended location. The results are shown in Fig. 12, where we can see that the focusing gain at the intended location is much larger than that at the unintended location, i.e., there exists a very good spatial focusing effect. In Fig. 12, we also observe some repetitive patterns. Such repetitive behavior is due to the representation of 2-D locations using 1-D index. To better illustrate the spatial focusing effect, we fix the intended location as the center of the test area and show in Fig. 13 the spatial focusing by directly using the real geographical locations. Clearly, we can see very good spatial focusing performance. Note that similar results are observed for all other intended locations.

We further evaluate the spatial focusing effect in a finer scale with 1-cm grid spacing, and the results are shown in Fig. 14. We can see that there is reasonably graceful degradation in terms of the spatial focusing effect within a 5 cm by 5 cm region, which is consistent with the fact that channels are uncorrelated with a half-wavelength spacing (the wavelength is around 5 cm when the carrier frequency is 5.4 GHz). In such a case, when a user is located between grid points with 10-cm spacing, it may not be localized correctly. Nevertheless, this can be easily solved by asking the user to rotate the device, e.g., smartphone, such that the antenna can cross the 10-cm grid points.

C. Localization Performance

From the results in the previous section, we can see that the CIR acts as a signature between the AP and the TD, and it drastically changes, even if the location is only 10 cm away. Here, we will examine the performance of our proposed indoor positioning algorithm.

To evaluate the performance, we use the leave-one-out cross validation. Specifically, we pick each CIR as the test sample and leave the rest as training samples in the database. Then, we perform our proposed algorithm, i.e., the online positioning algorithm, and evaluate the corresponding performance. There are totally 3016 CIRs for the 110 grid points, which leads to a total of 3016 trials. The localization performance is shown

TABLE I
LOCALIZATION PERFORMANCE WITH 10-CM LOCALIZATION ACCURACY

Number of Trials	3016
Number of Error	0
Error Rate	0%

in Table I, in which we can see that our proposed indoor localization algorithm gives zero error out of a total 3016 trials, which achieves 100% accuracy with no error in the 1 m by 0.9 m area of interest. Note that this result is achieved with a single AP working in the NLOS condition using one CIR.

D. Discussions

From the experimental results and discussions, we can see that the proposed TRIPS is an ideal solution to the indoor positioning problem since it can achieve very high localization accuracy with a very simple algorithm and low infrastructure cost summarized as follows.

- From the experimental results, we can see that, with a single AP working in the 5.4-GHz band under the NLOS condition, the proposed TRIPS can achieve perfect centimeter localization accuracy. Such localization accuracy is much better than that of existing state-of-the-art IPSs under the NLOS condition, which typically achieve meter-level localization accuracy. Moreover, the accuracy can be improved if we increase the resolution of the database, which, however, will increase the size of the database and, thus, the complexity of the online positioning algorithm.
- Based on the TR technique, the matching algorithm in our TRIPS is very simple, which just computes the TR resonating strength between the estimated CIR and that in the database. Compared with existing approaches, our method does not require complicated calibrations and matchings.
- Although the localization performance can be further improved with multiple APs, our method only uses a single AP and has already achieved very high localization accuracy under the NLOS condition. Moreover, no special apparatus is needed for the AP. Therefore, the infrastructure cost of our TRIPS is very low.
- The size of the database is determined by three factors, i.e., the room size, the resolution of the grid point, and the number of realizations at each grid point. For a typical room such as room "A" shown in Fig. 4(a), the size is 5.4 m by 3.1 m. Considering a resolution with 10-cm spacing between two neighboring grid points, there are a total of 1760 grid points. Suppose 20 CIR realizations are collected at each grid point, where the length of the channel L is 30 and where each tap of CIR is represented with 4 bytes (2 bytes for the real part and 2 bytes for the imaginary part). Then, the size of the database is $1760 \times 20 \times 30 \times 4 = 4\,224\,000$ bytes (4.2 MB). Such a database is reasonably small, which can be easily stored with an off-the-shelf storage device. Moreover, all system configurations, including the grid size, the number of realizations, and the channel length L, are all adjustable to fit a specific environment at a desired localization performance.
- The proposed TRIPS is not limited to the 5.4-GHz band. It can be also applied to the ultrawide band with a larger bandwidth, where we expect to achieve much higher localization accuracy.

IV. CONCLUSION

In this paper, we have proposed a TRIPS by exploiting the unique location-specific characteristic of CIR. Specifically, we have addressed the ill-posed single-AP localization problem by decomposing it into two well-defined subproblems. One subproblem is calibration by building a database that maps the physical geographical locations to the logical locations in the CIR space, and the other subproblem is matching the estimated CIR with those in the database. We built a real prototype to evaluate the proposed scheme. Experimental results show that, even only with a single AP under the NLOS condition and a single realization of online measurements, the proposed scheme can still achieve 100% localization accuracy at the scale of 10 cm within a 0.9 m by 1 m area of interest.

REFERENCES

[1] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Trans. Syst., Man, Cybern., Part C: Appl. Rev.*, vol. 37, no. 6, pp. 1067–1080, Nov. 2007.

[2] M. Youssef, A. Youssef, C. Rieger, U. Shankar, and A. Agrawala, "Pinpoint: An asynchronous time-based location determination system," in *Proc. 4th Int. Conf. MobiSys., Appl. Services*, New York, NY, USA, 2006, pp. 165–176, ACM.

[3] R. J. Fontana and S. J. Gunderson, "Ultra-wideband precision asset location system," in *Proc. IEEE Conf. Ultra Wideband Syst. Technol., Dig. Papers*, May 2002, pp. 147–150.

[4] D. Niculescu and B. Nath, "Vor base stations for indoor 802.11 positioning," in *Proc. 10th Annu. Int. Conf. MobiCom*, New York, NY, USA, 2004, pp. 58–69, ACM.

[5] J. Xiong and K. Jamieson, "Arraytrack: A fine-grained indoor location system," in *Proc. 10th USENIX Symp. NSDI*, Lombard, IL, USA, 2013, pp. 71–84, USENIX.

[6] Y. Zhao, "Standardization of mobile phone positioning for 3g systems," *IEEE Commun. Mag.*, vol. 40, no. 7, pp. 108–116, Jul. 2002.

[7] G. Sun, J. Chen, W. Guo, and K. J. R. Liu, "Signal processing techniques in network-aided positioning: A survey of state-of-the-art positioning designs," *IEEE Signal Process. Mag.*, vol. 22, no. 4, pp. 12–23, Jul. 2005.

[8] A. Kushki, K. N. Plataniotis, and A. N. Venetsanopoulos, "Kernel-based positioning in wireless local area networks," *IEEE Trans. Mobile Comput.*, vol. 6, no. 6, pp. 689–705, Jun. 2007.

[9] P. Bahl and V. N. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proc. IEEE INFOCOM. 19th Annu. Joint Conf. IEEE Comput. Commun. Soc.*, 2000, vol. 2, pp. 775–784.

[10] J. Koo and H. Cha, "Localizing wifi access points using signal strength," *IEEE Commun. Lett.*, vol. 15, no. 2, pp. 187–189, Feb. 2011.

[11] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *IEEE Trans. Mobile Comput.*, vol. 11, no. 12, pp. 1983–1993, Dec 2012.

[12] M. A. Youssef, A. Agrawala, and A. Udaya Shankar, "Wlan location determination via clustering and probability distributions," in *Proc. 1st IEEE Int. Conf. PerCom*, Mar. 2003, pp. 143–150.

[13] M. Youssef and A. Agrawala, "The horus wlan location determination system," in *Proc. 3rd Int. Conf. MobiSys, Appl., Serv.*, New York, NY, USA, 2005, pp. 205–218, ACM.

[14] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha, "Indoor localization using fm signals," *IEEE Trans. Mobile Comput.*, vol. 12, no. 8, pp. 1502–1517, Aug. 2013.

[15] Y. Jin, W.-S. Soh, and W.-C. Wong, "Indoor localization with channel impulse response based fingerprint and nonparametric regression," *IEEE Trans. Wireless Commun.*, vol. 3, no. 9, pp. 1120–1127, Mar. 2010.

[16] N. Patwari and S. K. Kasera, "Robust location distinction using temporal link signatures," in *Proc. 13th Annu. ACM Int. Conf. MobiCom*, 2007, pp. 111–122.

[17] J. Zhang, M. H. Firooz, N. Patwari, and S. K. Kasera, "Advancing wireless link signatures for location distinction," in *Proc. 14th ACM Int. Conf. MobiCom*, 2008, pp. 26–37.

[18] K. Wu *et al.*, "Csi-based indoor localization," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 7, pp. 1300–1309, Jul. 2013.

[19] B. Wang, Y. Wu, F. Han, Y.-H. Yang, and K. J. R. Liu, "Green wireless communications: A time-reversal paradigm," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 8, pp. 1698–1710, Sep. 2011.

[20] B. I. Zeldovich, N. F. Pilipetskii, and V. V. Shkunov, "Principles of phase conjugation," in *Springer Series in Optical Sciences*. New York, NY, USA: Springer-Verlag, vol. 42, p. 262, 1985.

[21] M. Fink, C. Prada, F. Wu, and D. Cassereau, "Self focusing in inhomogeneous media with time reversal acoustic mirrors," in *Proc. IEEE Ultrason. Symp.*, Oct. 1989, vol. 2, pp. 681–686.

[22] M. Fink, "Time reversal of ultrasonic fields. i. basic principles," *IEEE Trans. Ultrason., Ferroelectr. Freq. Control*, vol. 39, no. 5, pp. 555–566, Sep. 1992.

[23] A. Derode, P. Roux, and M. Fink, "Robust acoustic time reversal with high-order multiple scattering," *Phys. Rev. Lett.*, vol. 75, pp. 4206–4209, Dec 1995.

[24] G. F. Edelmann *et al.*, "An initial demonstration of underwater acoustic communication using time reversal," *IEEE J. Ocean. Eng.*, vol. 27, no. 3, pp. 602–609, Jul. 2002.

[25] B. E. Henty and D. D. Stancil, "Multipath-enabled super-resolution for rf and microwave communication using phase-conjugate arrays," *Phys. Rev. Lett.*, vol. 93, no. 24, Dec. 2004, Art. ID. 243904.

[26] G. Lerosey *et al.*, "Time reversal of electromagnetic waves," *Phys. Rev. Lett.*, vol. 92, May 2004, Art. ID. 193904.

[27] R. C. Qiu, C. Zhou, N. Guo, and J. Q. Zhang, "Time reversal with miso for ultrawideband communications: Experimental results," *IEEE Antennas Wireless Propag. Lett.*, vol. 5, no. 1, pp. 269–273, Dec. 2006.

[28] G. Lerosey *et al.*, "Time reversal of electromagnetic waves and telecommunication," *Radio Sci.*, vol. 40, no. 6, Dec. 2005.

[29] G. Lerosey, J. De Rosny, A. Tourin, A. Derode, and M. Fink, "Time reversal of wideband microwaves," *Appl. Phys. Lett.*, vol. 88, no. 15, pp. 154101-1–154101-3, Apr. 2006.

[30] I. H. Naqvi *et al.*, "Experimental validation of time reversal ultra wideband communication system for high data rates," *Microw., Antennas Propag., IET*, vol. 4, no. 5, pp. 643–650, May 2010.

[31] J. De Rosny, G. Lerosey, and M. Fink, "Theory of electromagnetic time-reversal mirrors," *IEEE Trans. Antennas Propag.*, vol. 58, no. 10, pp. 3139–3149, Oct. 2010.

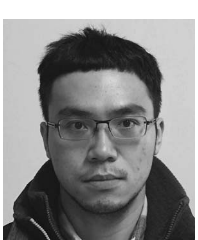
[32] F. Han, Y.-H. Yang, B. Wang, Y. Wu, and K. J. R. Liu, "Time-reversal division multiple access over multi-path channels," *IEEE Trans. Commun.*, vol. 60, no. 7, pp. 1953–1965, Jul. 2012.

[33] Y. H. Yang, B. Wang, W. S. Lin, and K. J. R. Liu, "Near-optimal waveform design for sum rate optimization in time-reversal multiuser downlink systems," *IEEE Trans. Wireless Commun.*, vol. 12, no. 1, pp. 346–357, Jan. 2013.

[34] Y. Chen, Y. H. Yang, F. Han, and K. J. R. Liu, "Time-reversal wideband communications," *IEEE Signal Process. Lett.*, vol. 20, no. 12, pp. 1219–1222, Dec. 2013.

[35] F. Han and K. J. R. Liu, "A multiuser TRDMA uplink system with 2-D parallel interference cancellation," *IEEE Trans. Commun.*, vol. 62, pp. 1011–1022, Mar. 2014.

[36] Y. Chen *et al.*, "Time-reversal wireless paradigm for green Internet of things: An overview," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 81–98, Feb. 2014.



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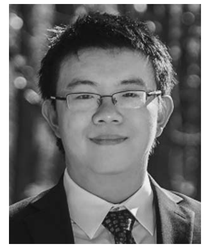

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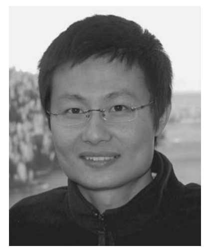

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